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17 June 2015

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

From global climate prediction to climate services

Francisco Doblas-Reyes

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

The BSC Earth Sciences Dept.

What

Environmental forecasting

… research …
… operations …
… services …
… high resolution …

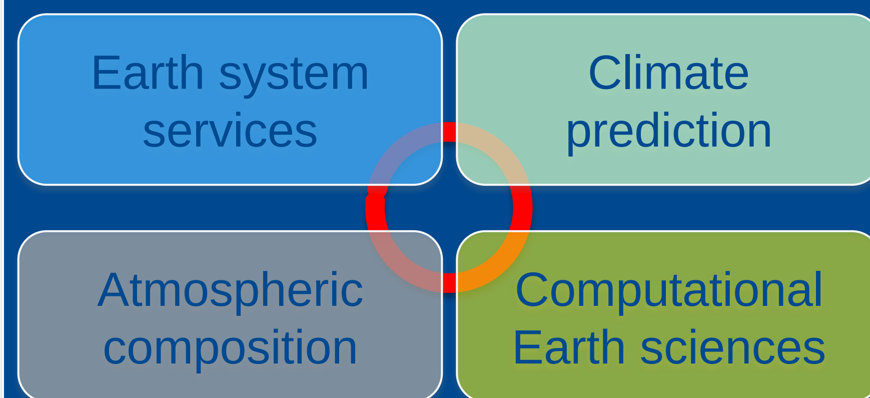
How

Develop a capability to model air quality processes from urban to global and the impacts on weather, health and ecosystems

Implement climate prediction system for subseasonal-to-decadal climate prediction

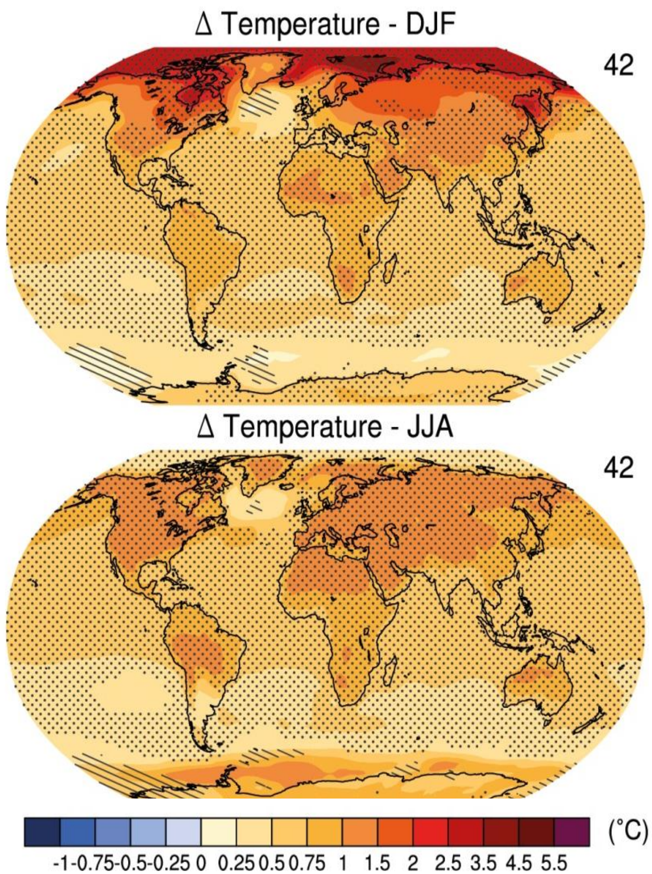
Develop user-oriented services that favour both technology transfer and adaptation

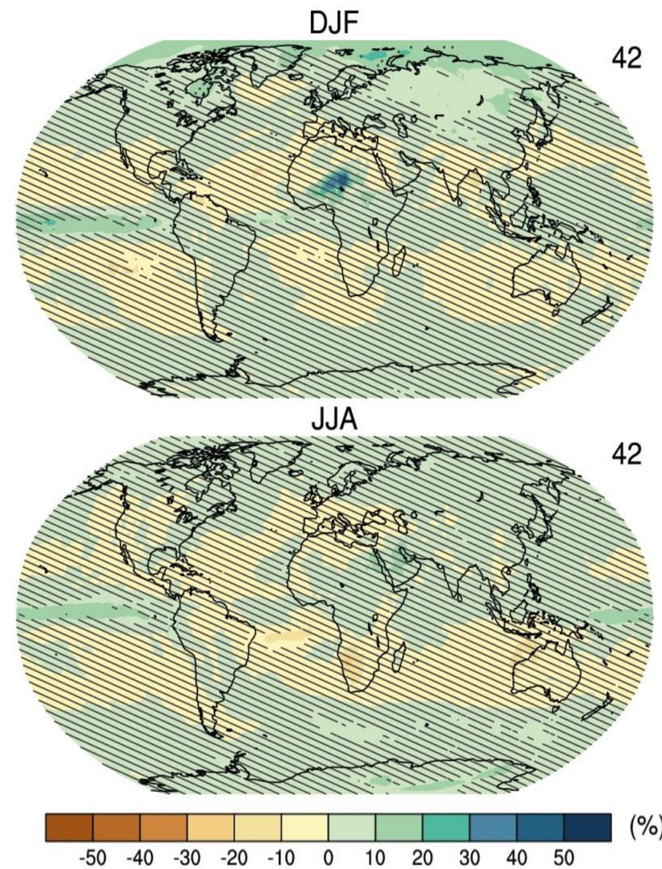
Use cutting-edge HPC and Big Data technologies for the efficiency and user-friendliness of Earth system models



What is coming up for climate?

Seasonal-mean air temperature and percentage precipitation change for the RCP4.5 scenario from CMIP5 over 2016-2035 (wrt 1986-2005). Stippling for significant changes, hatching for non-significant.

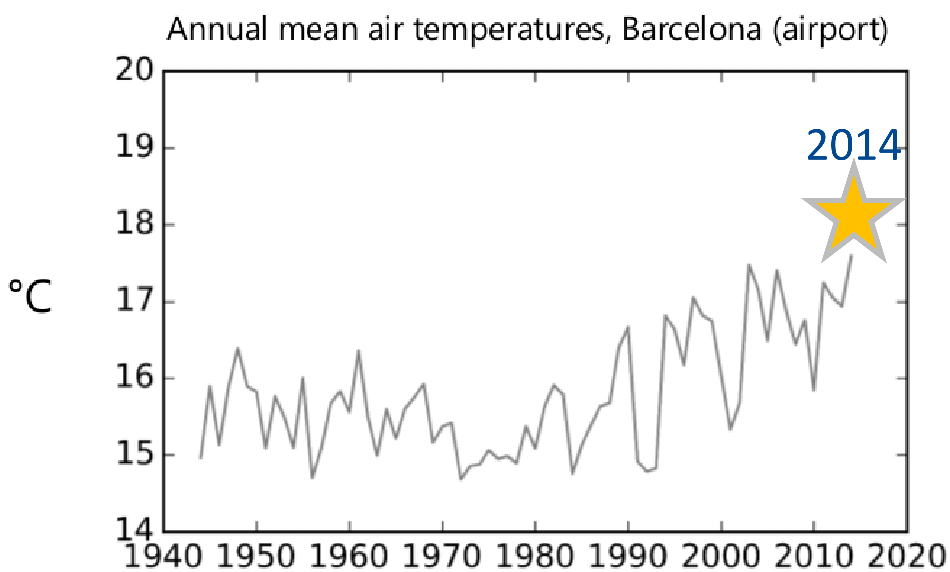


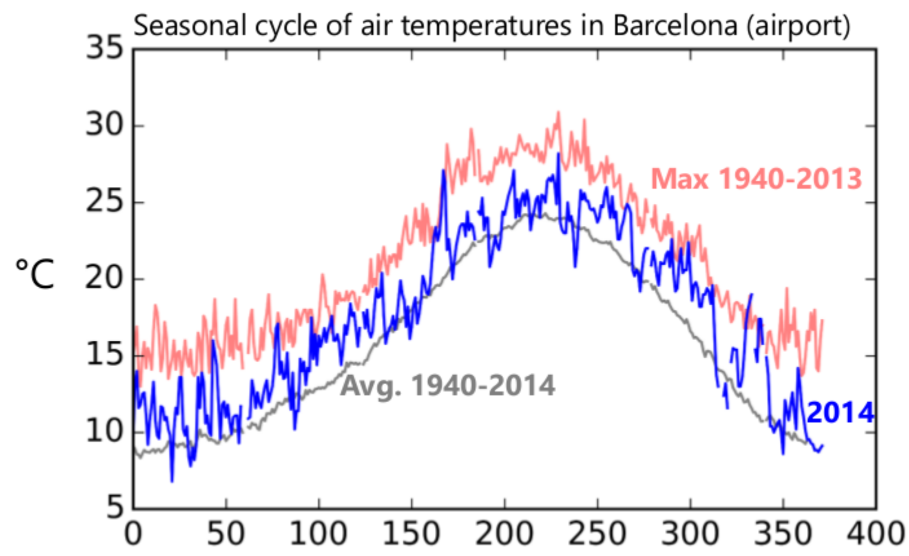


IPCC AR5 WGI (2013)

A local example of what people ask

Temperatures in Barcelona airport from the ECAD dataset.





François Massonnet (IC3)

A more complex example

Bodegas Torres (a Spanish winery) is looking for new locations for its vineyards (and it's not the only one doing it).

Land is being purchased closer to the Pyrenees, at higher elevation. They are considering acquiring land in South America too, in areas where wine is currently not produced.

Bodegas Torres requests local climate information (including appropriate uncertainty assessments) for the vegetative cycle of the vine, which lasts 30-40 years.

Some users need to make the decision now.

Climate services is just a concept, predictions and projections are just a tool

Adaptation using seamless sources

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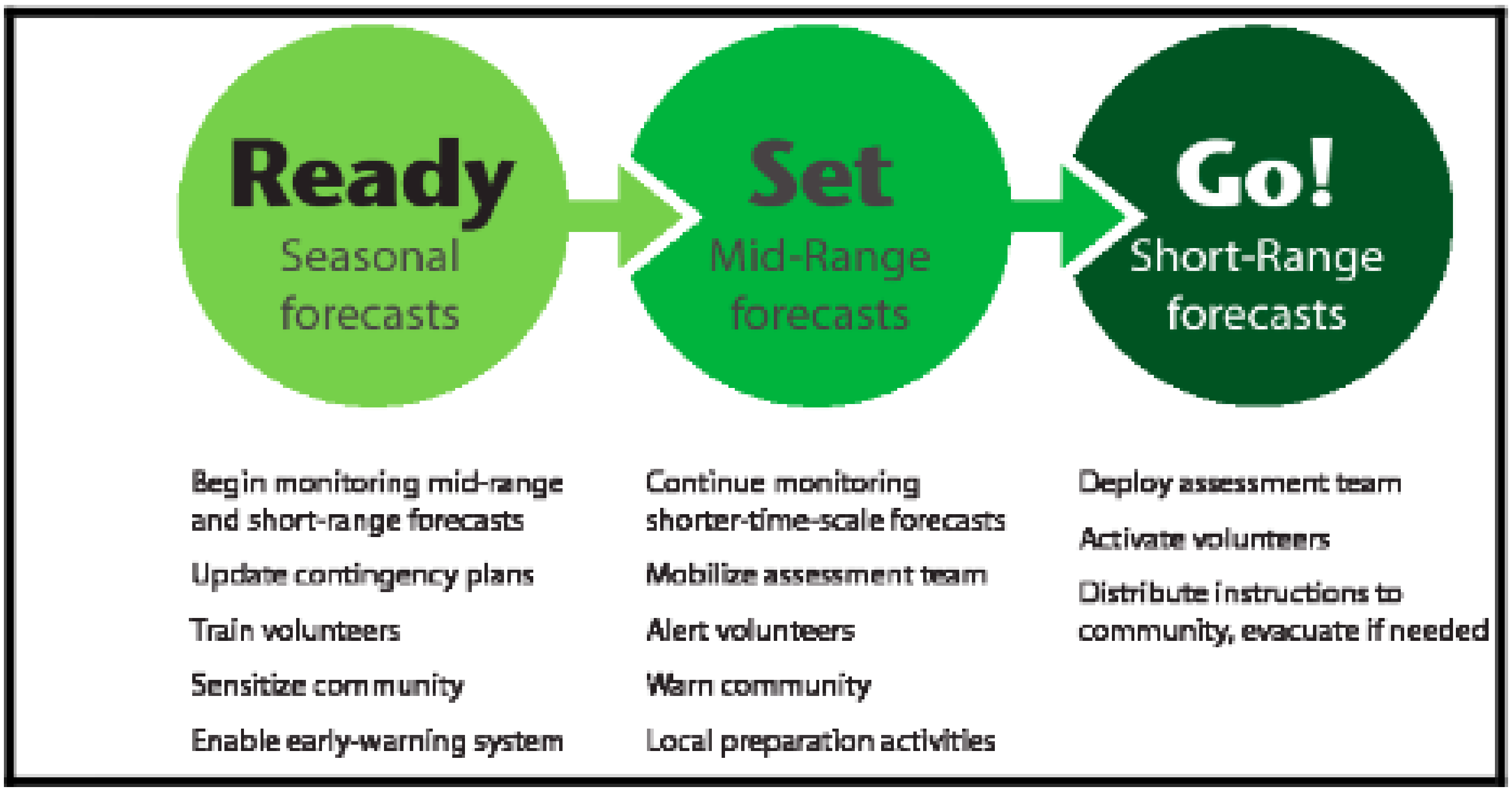
Application of seamless climate and weather information. Example from the IRI-Red Cross collaboration.



IRI

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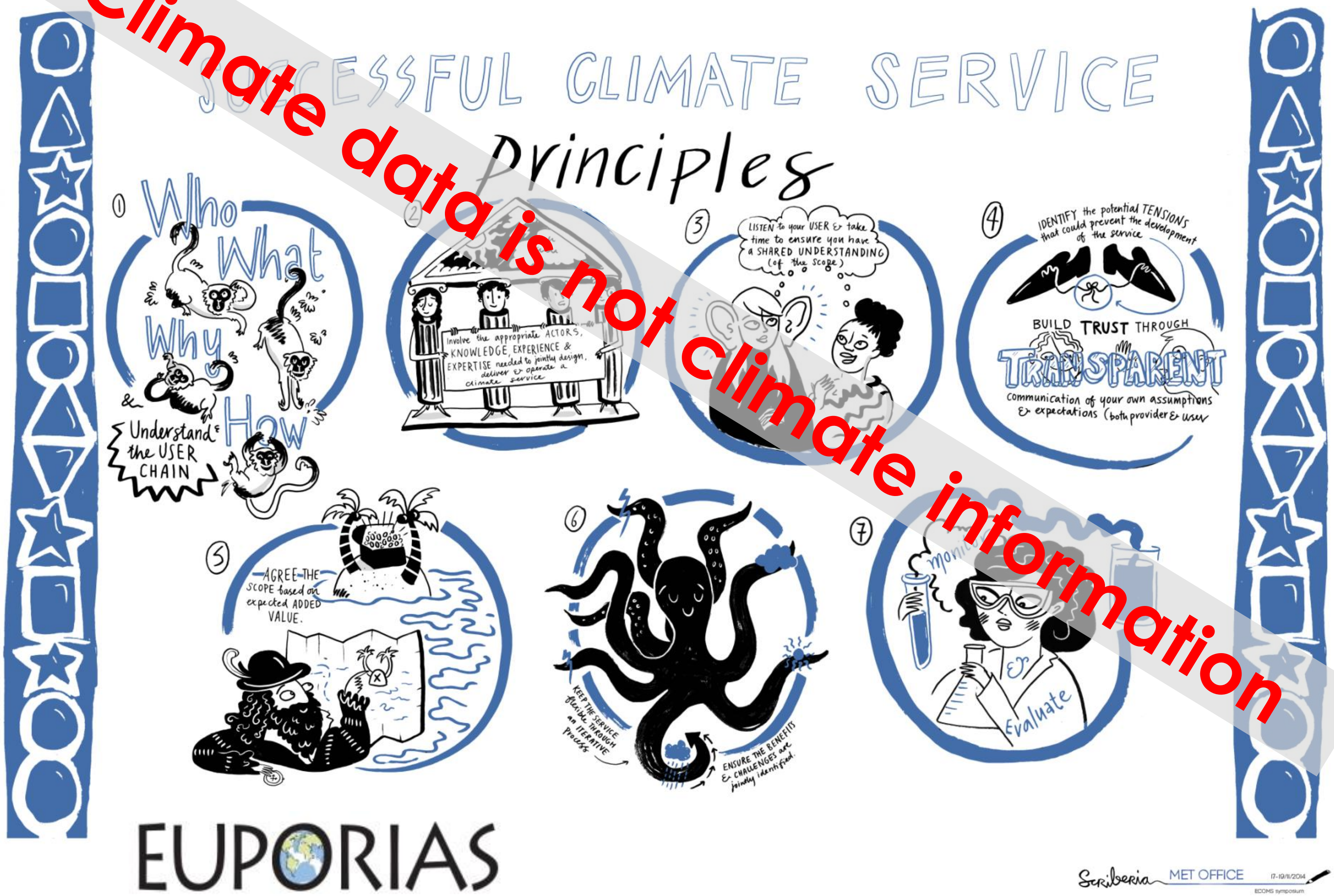
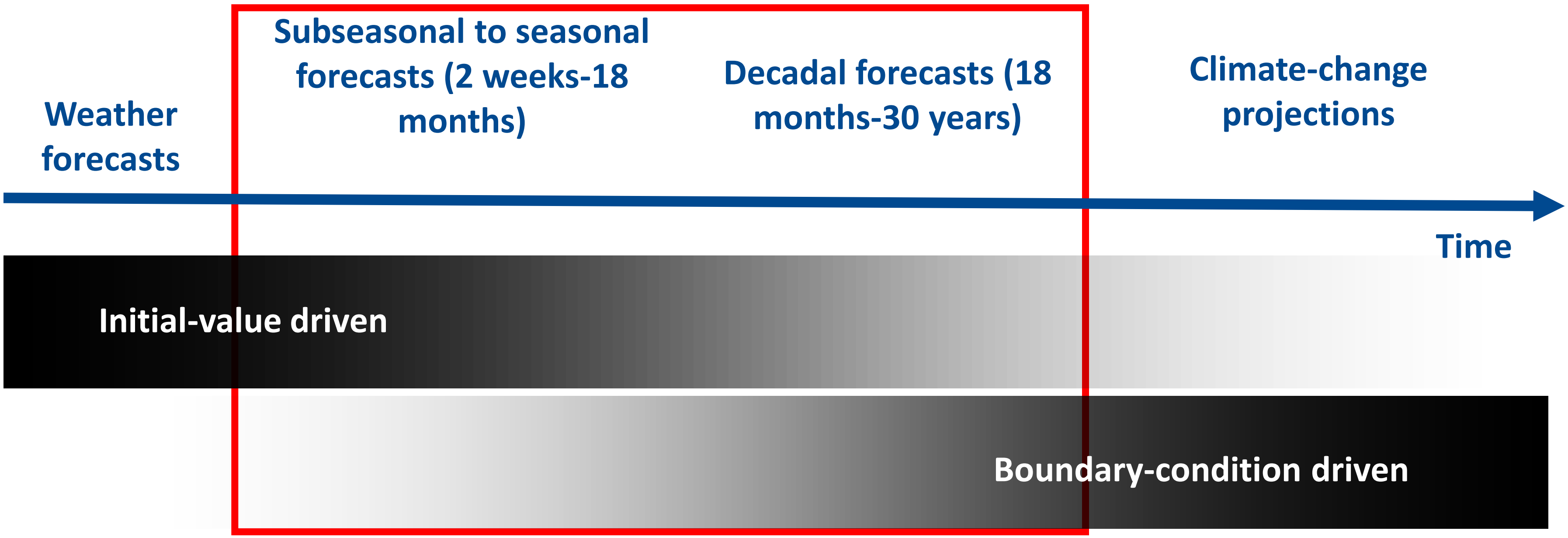
Climate data is not climate information.



Climate data is not climate information

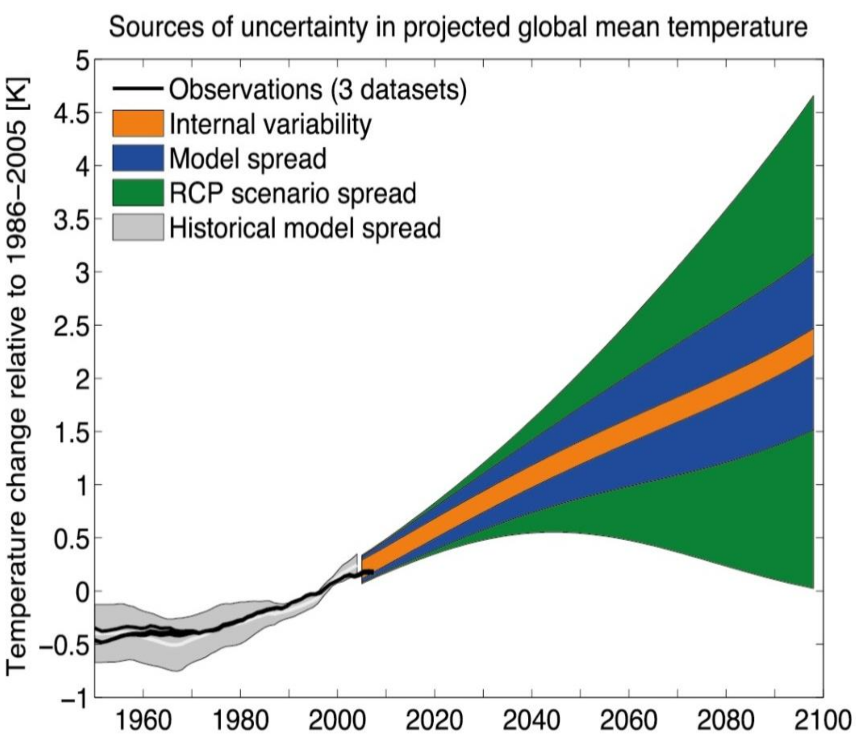
Climate prediction time scales

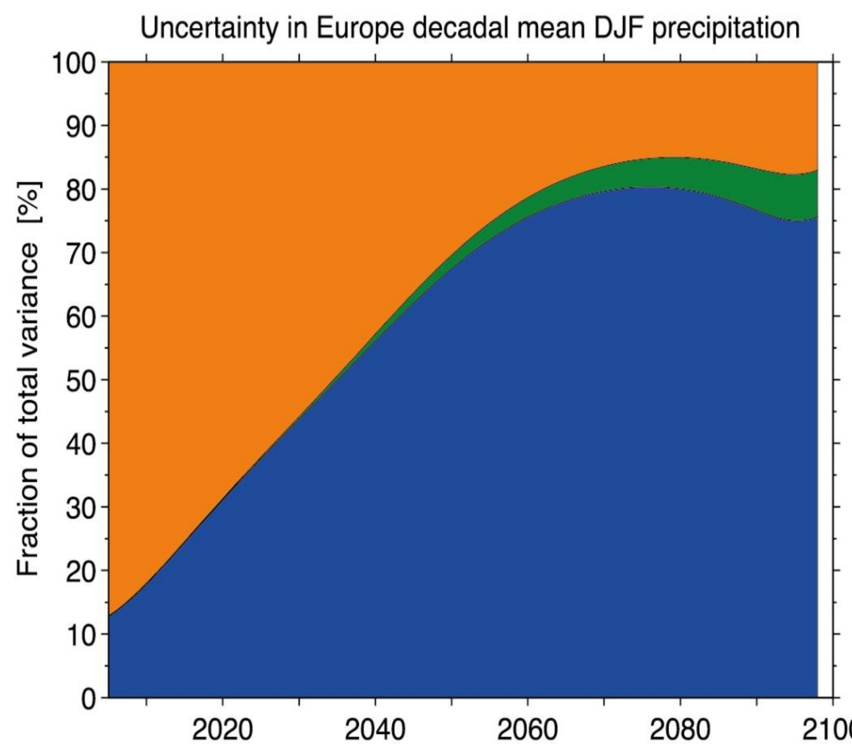
Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and systematic comparison with a simultaneous reference.



Adapted from Meehl et al. (2009)

The sources of uncertainty include the internal variability, model differences and scenario spread. The internal variability is an uncertainty source particularly important for the near term that could be reduced, especially at regional scales.





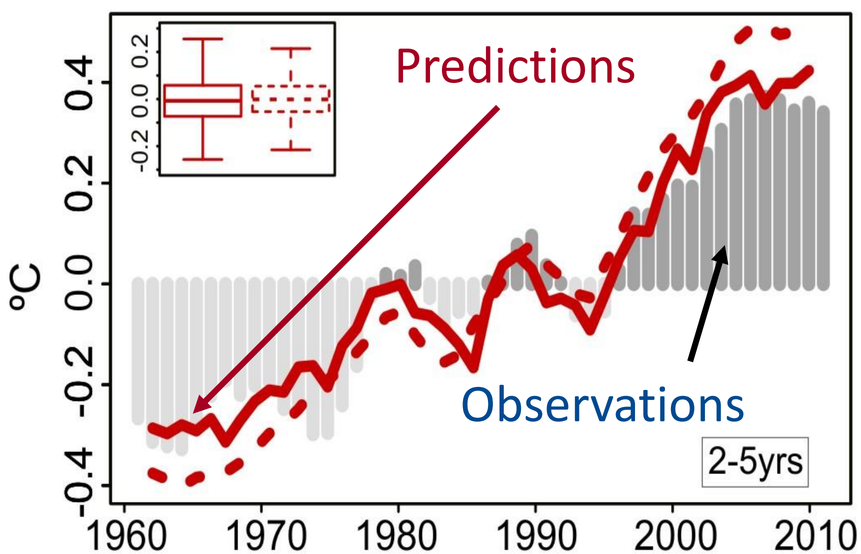
IPCC AR5 WGI (2013)

CMIP5 decadal predictions

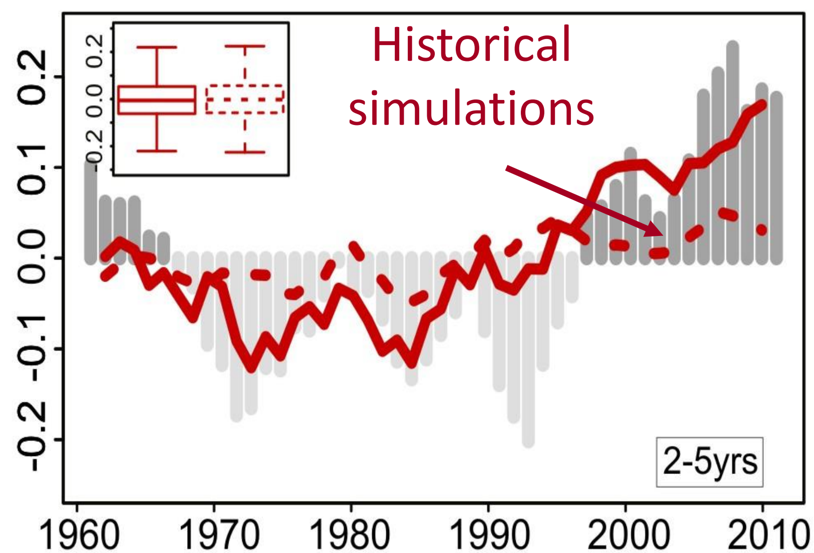
CMIP5 decadal predictions. Global-mean near-surface air temperature and AMV against GHCN/ERSST3b for forecast years 2-5.

The initialized experiments reproduce the GMST trends and the AMV variability and suggest that initialization corrects the forced model response and phases in some of the internal variability.

Global mean surface air temperature (GMST)



Atlantic multidecadal variability (AMV)



Doblas-Reyes et al. (2013, Nat. Comms.)

CMIP5 decadal predictions

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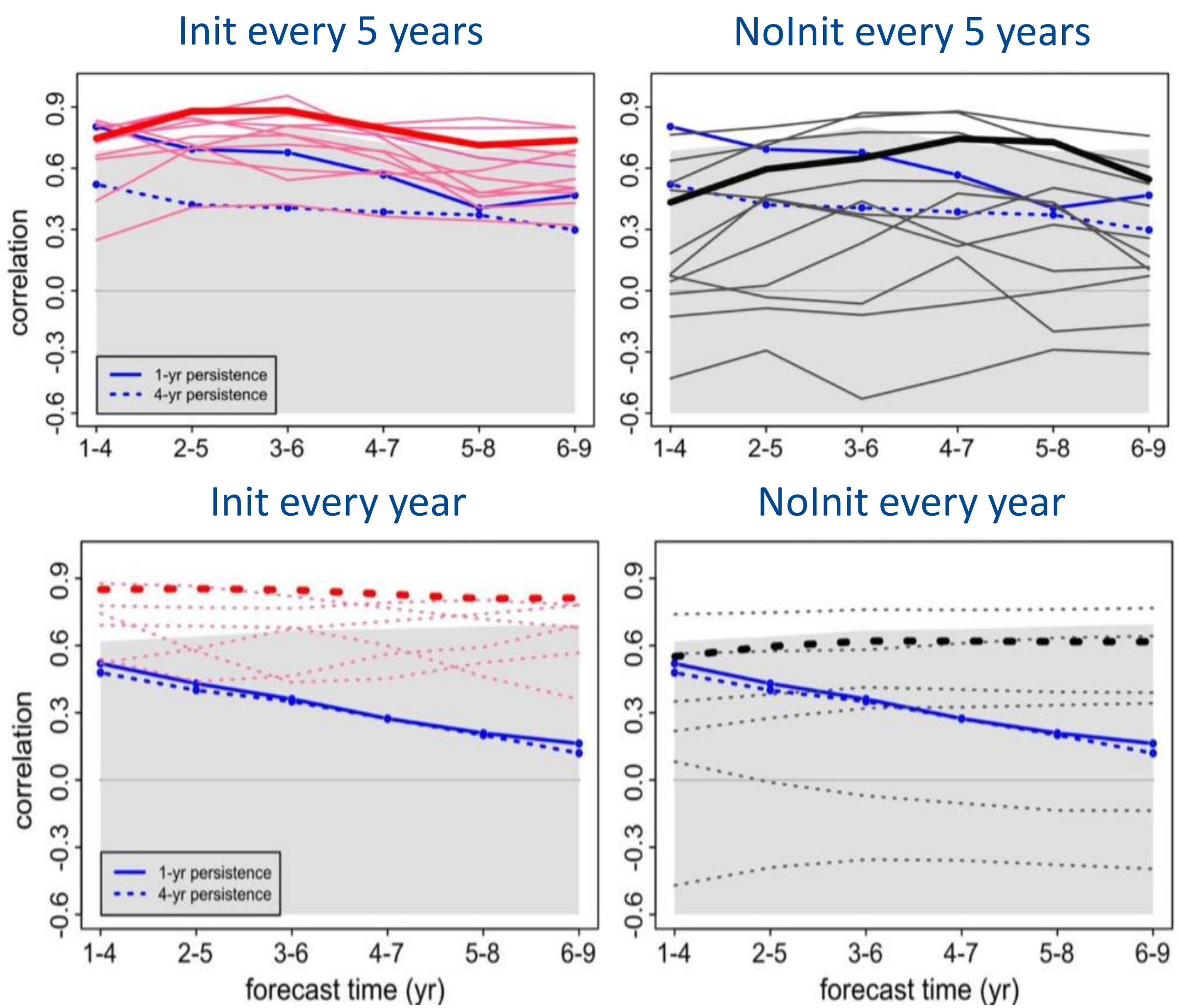
Correlation of the ensemble mean of the AMV against GHCN/ERSST3b as a function of forecast time.

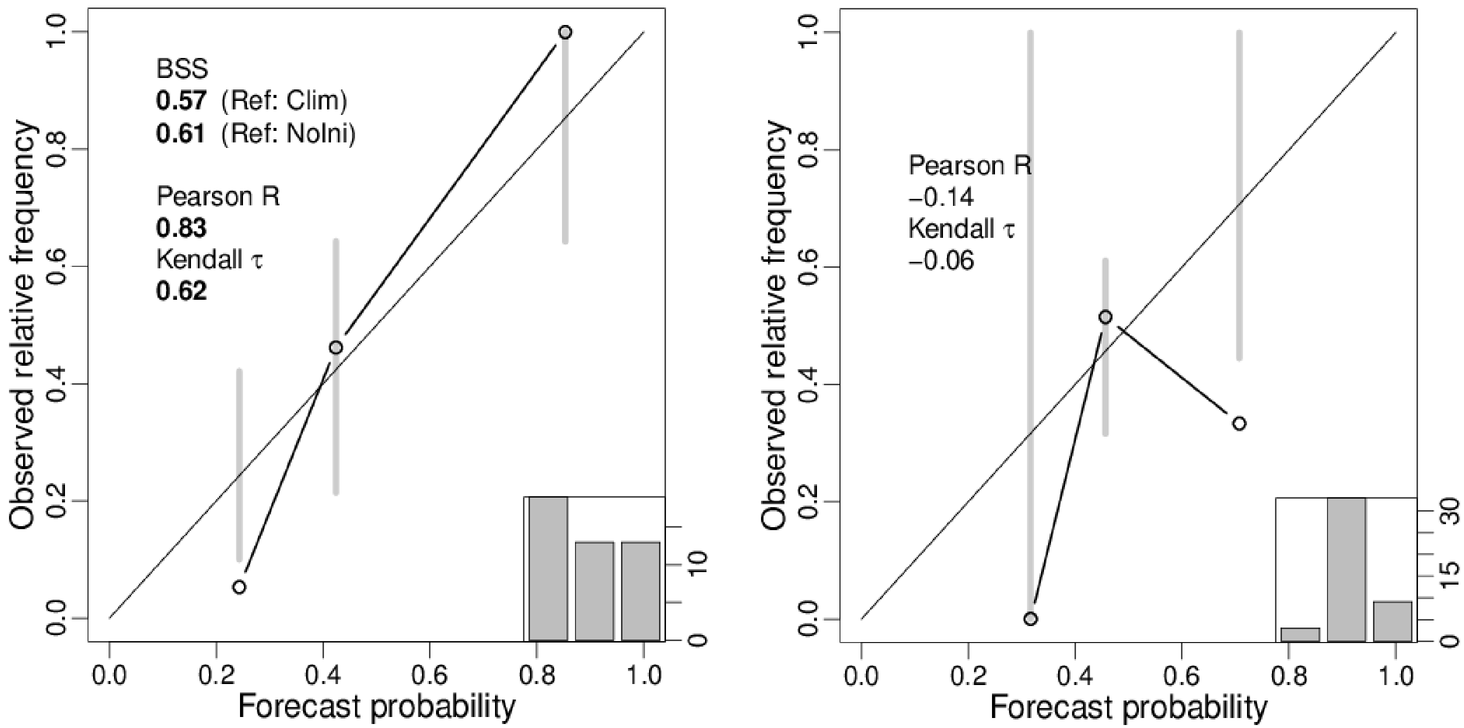


García-Serrano et al. (2014, Clim. Dyn.)

CMIP5: Service-driven predictions

Reliability diagrams of left) initialised and right) uninitialised MME simulations for basin-wide **accumulated cyclone energy** (ACE). The results are for 2-9 year averages above the climatological median over 1961-2009. Statistically significant values are in bold.

Some of the added value of the predictions is their better management of uncertainty, which leads to increased **credibility**.



Caron et al. (2015, GRL)

CMIP5: Predictions with large impact

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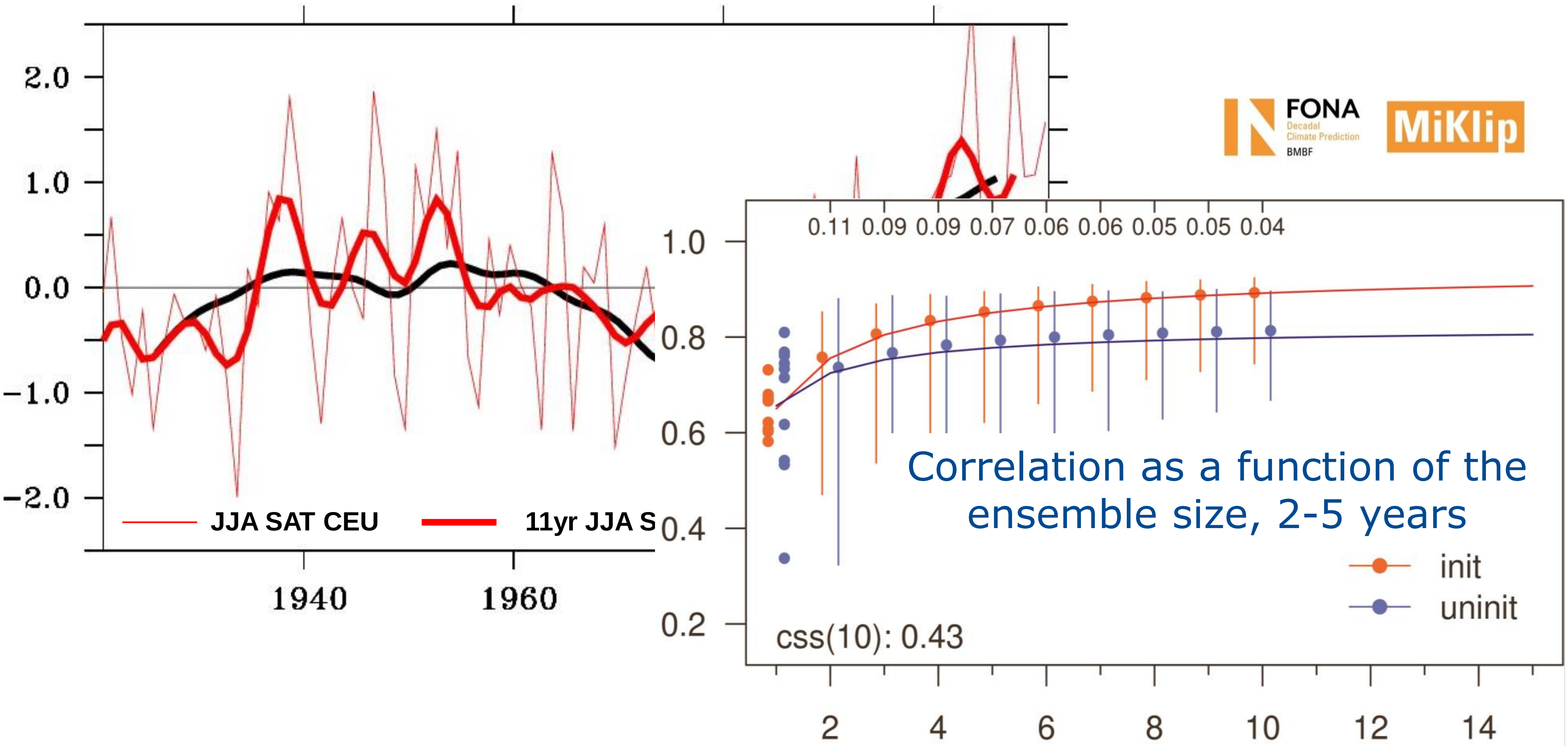
Time series of central European summer temperature and skill of the MiKlip system.



W. Müller (MPI)

The climate prediction drift issue

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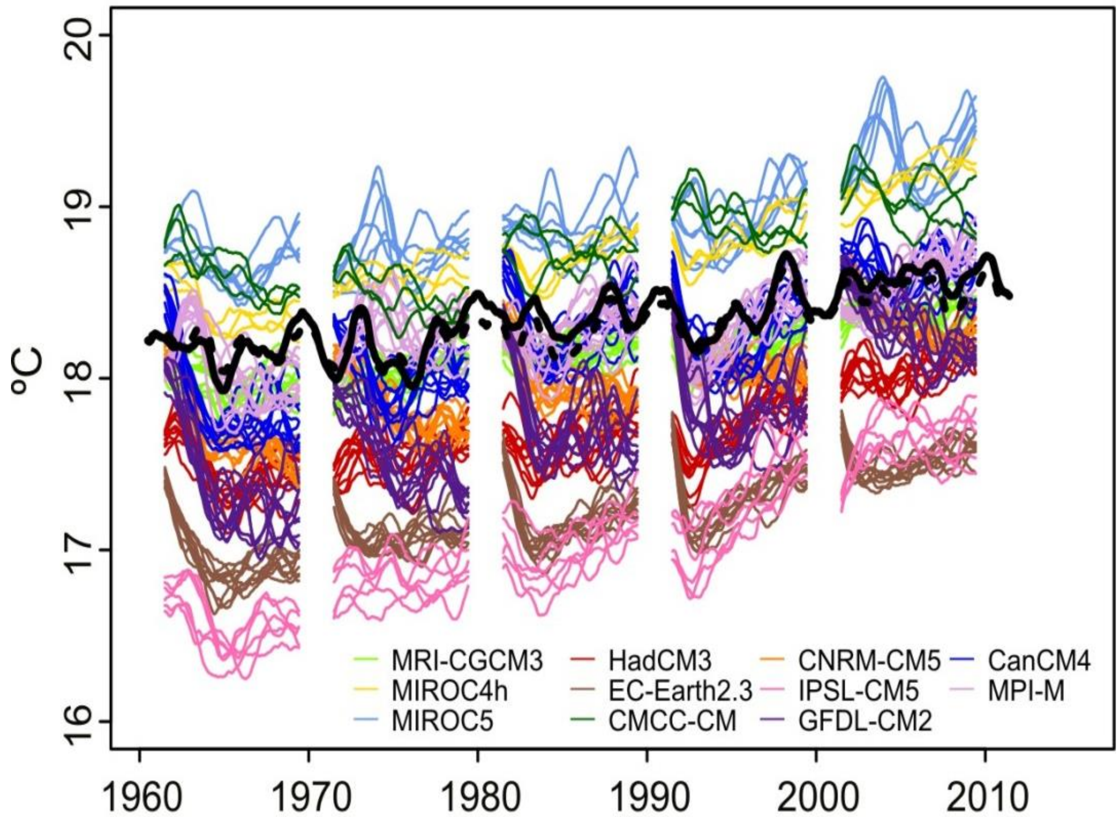
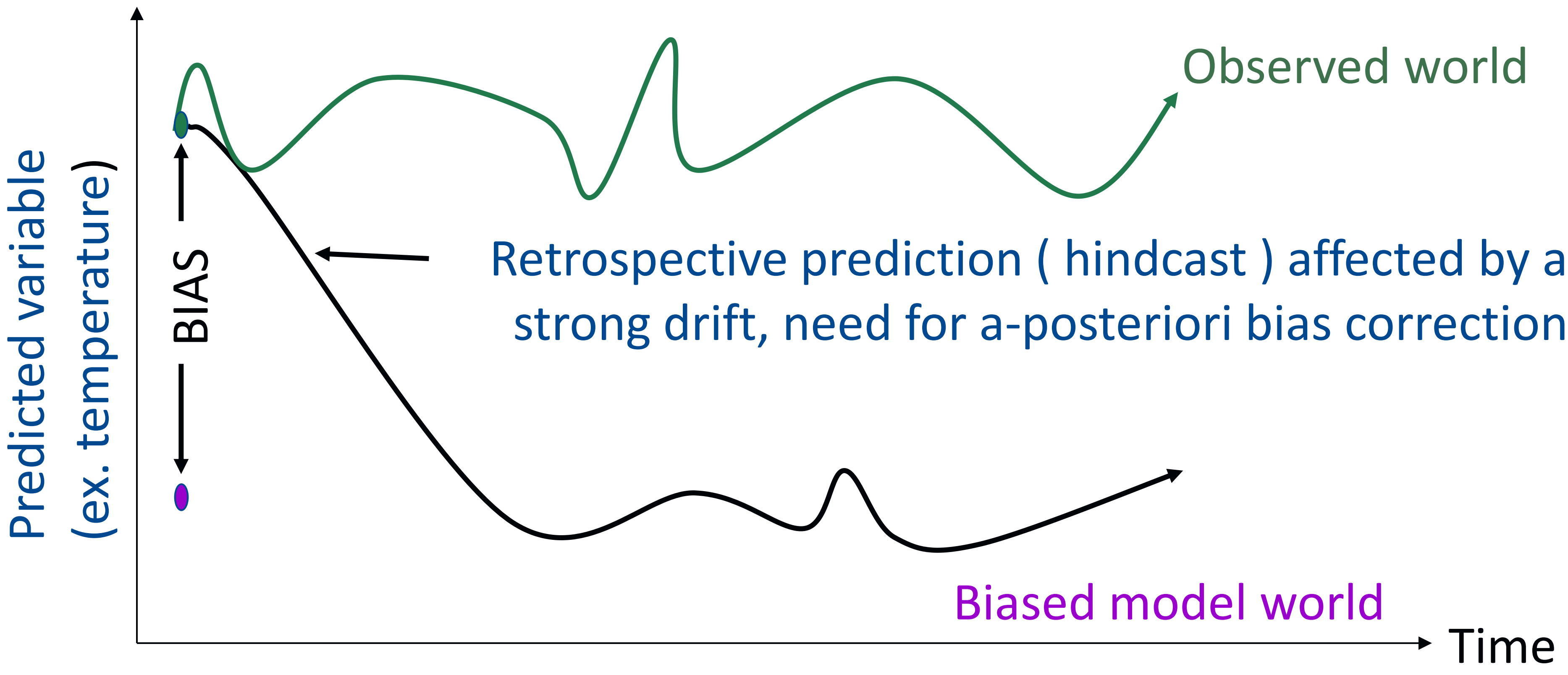
Global mean near-surface air temperature over the ocean (one-year running mean applied) from CMIP5 hindcasts. Each system is shown with a different colour. NCEP and ERA40/Int used as reference.

Examples of shock, drift and large systematic error can be found.

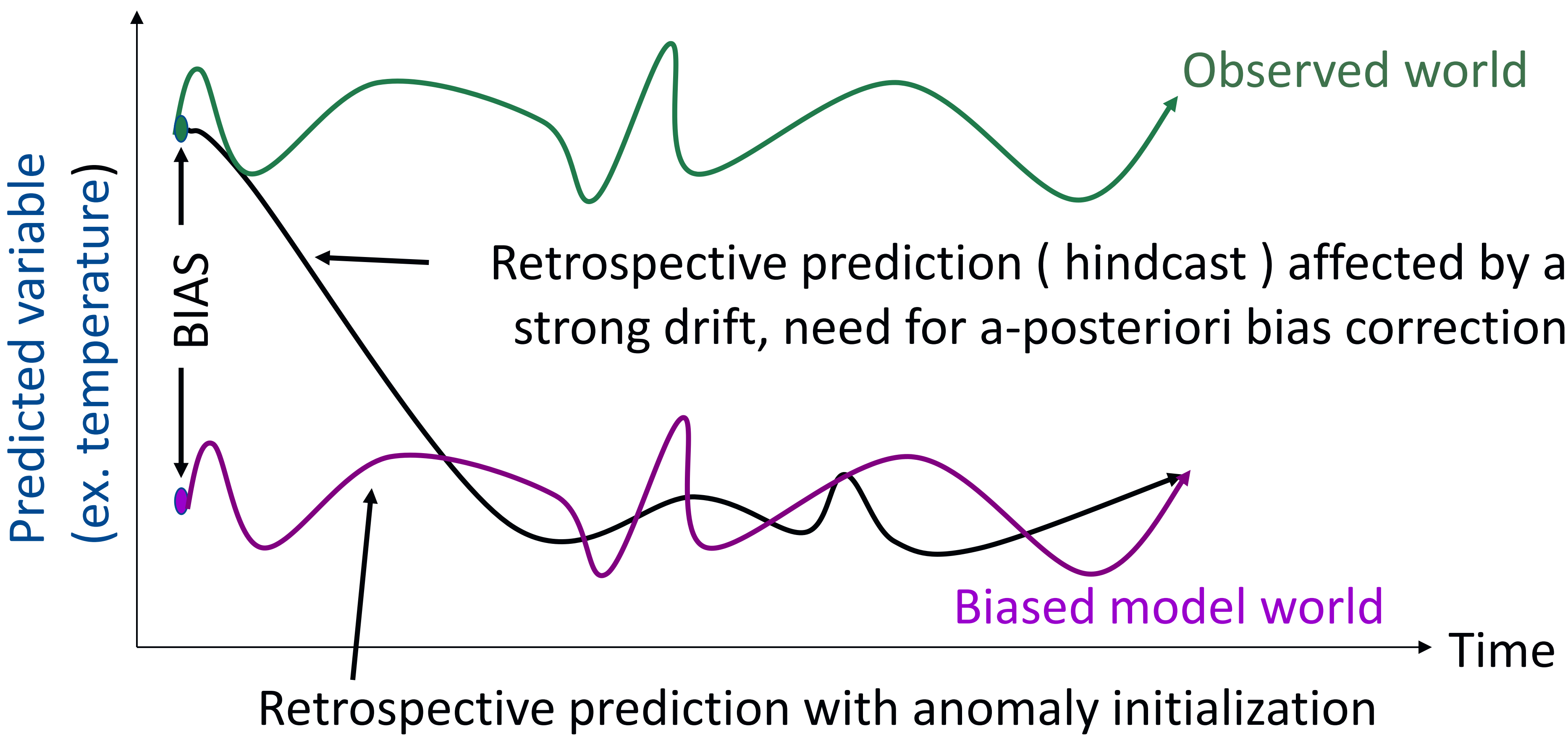


IPCC AR5 WGI (2013)

The climate prediction drift issue



The climate prediction drift issue

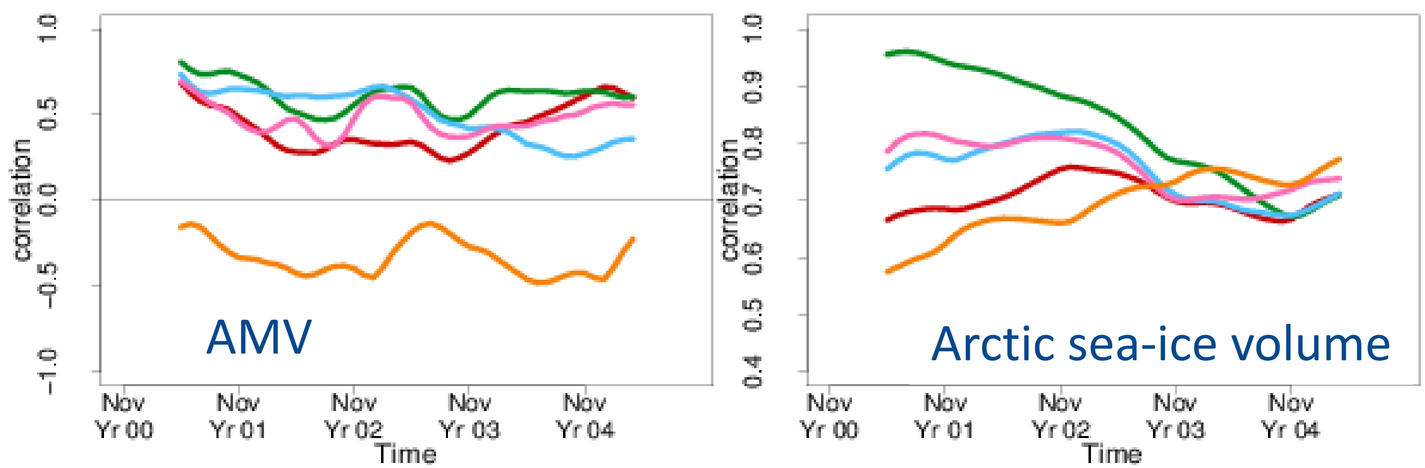


Initialization approaches

Assessment of full-field (red), anomaly in the ocean (blue), weighted anomaly in the ocean and the sea ice, with initialisation of temperature and density instead of the usual temperature and salinity (green), and a weighted anomaly nudging in the ocean (pink).

Decadal prediction experiments run with EC-Earth2.3. Comparison with historical ensemble simulation (orange). 5 ensemble members, one start date every 2 years.

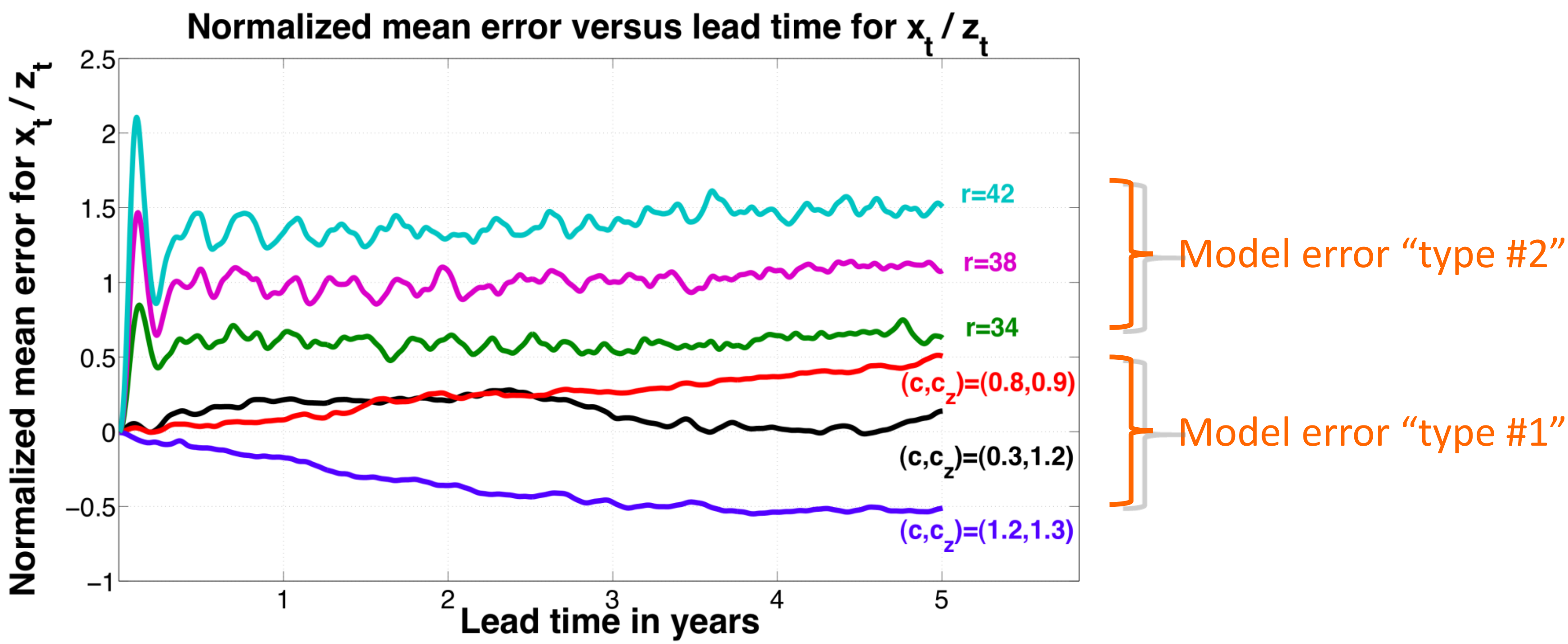
Reference data: ERSST data for AMO and SST, sea-ice reconstruction from Guemas et al. 2013 for sea-ice area and volume.



Volpi et al. (2015, Clim. Dyn.)

Initialization: back to simple models

Mean error of two variables from 360 decadal predictions performed with the Lorenz model with three compartments (ocean, tropical atmosphere and extra-tropical atmosphere). The configurations where AI outperforms FFI are associated with a strong initial shock and a larger bias.

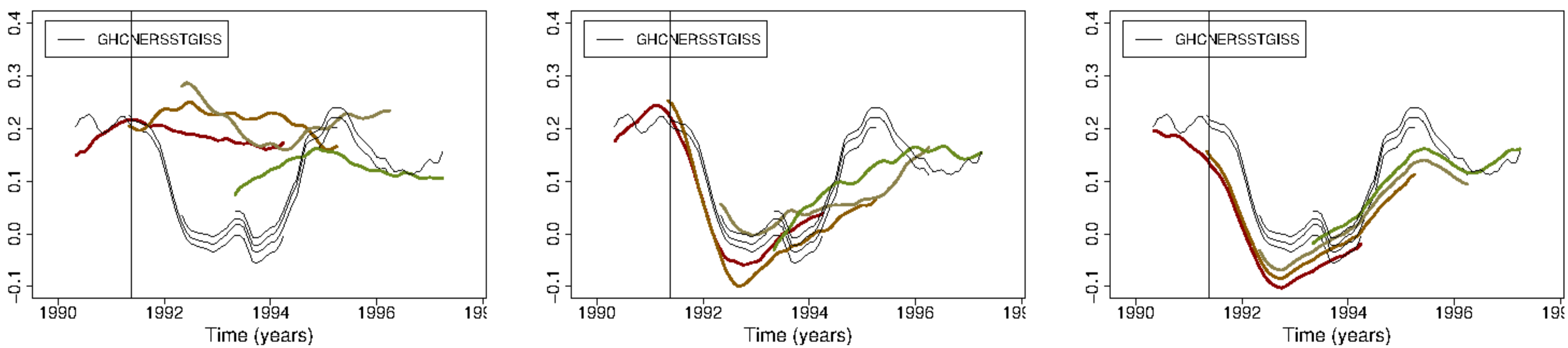


Carrassi et al. (2014, NPG)

Beyond GHG: Volcanic aerosol

Global-mean surface temperature before and after the Pinatubo eruption simulated by EC-Earth 2.3 with five-member ensemble hindcasts. Observational data is a mix between GHCN, ERSST and GISS.

Both the initialisation and the volcanic forcing specification improve the simulations but **a solution is needed to prescribe the aerosol during the forecasts**.

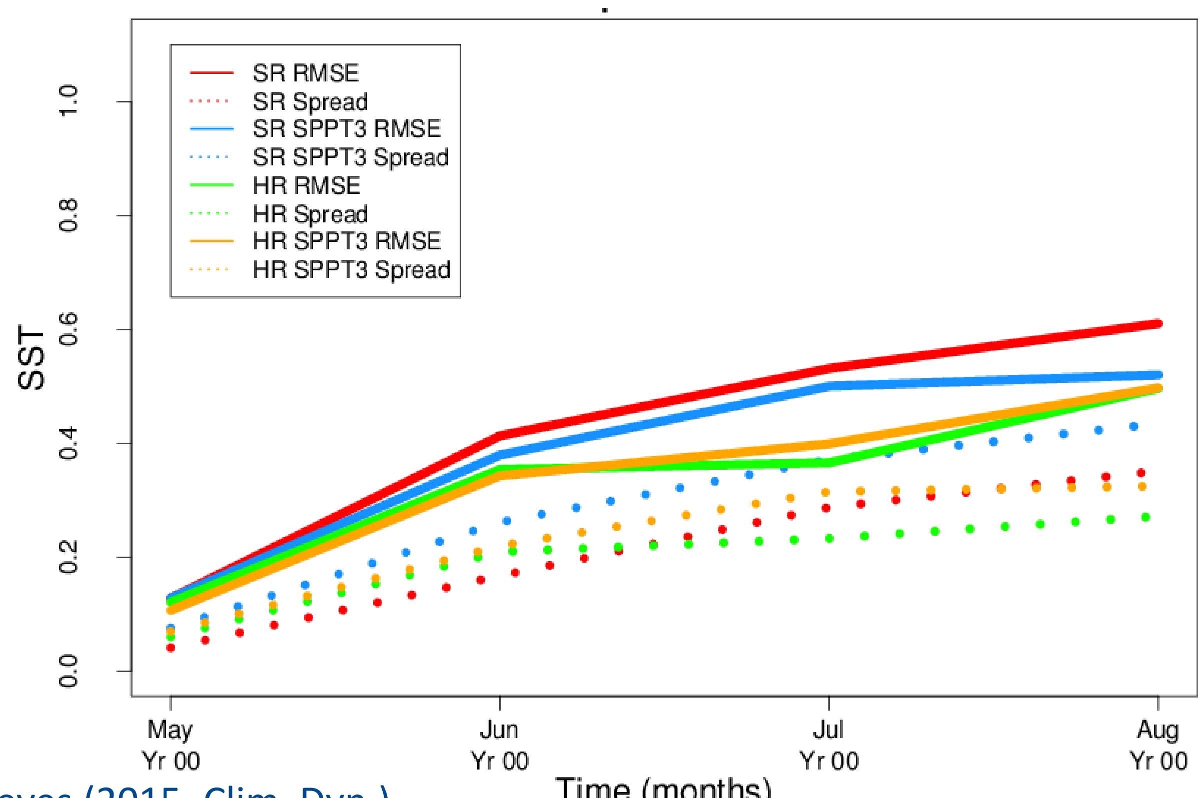


Initialisation and no volcanoes — Initialisation and volcanoes — No initialisation and volcanoes

M. Ménégoz (IC3)

High resolution has been thoroughly tested in climate prediction mode. The same applies to the stochastic physics.

RMSE and spread of Niño3.4 SST (versus ERSST) from EC-Earth3 simulations: standard resolution (**SR, T255/ORCA1**), high resolution (**HR, T511/ORCA025**) without and with stochastic physics (**SPPT3**). May start dates over 1993-2009 using ERA-Interim and GLORYS and ten-member ensembles.



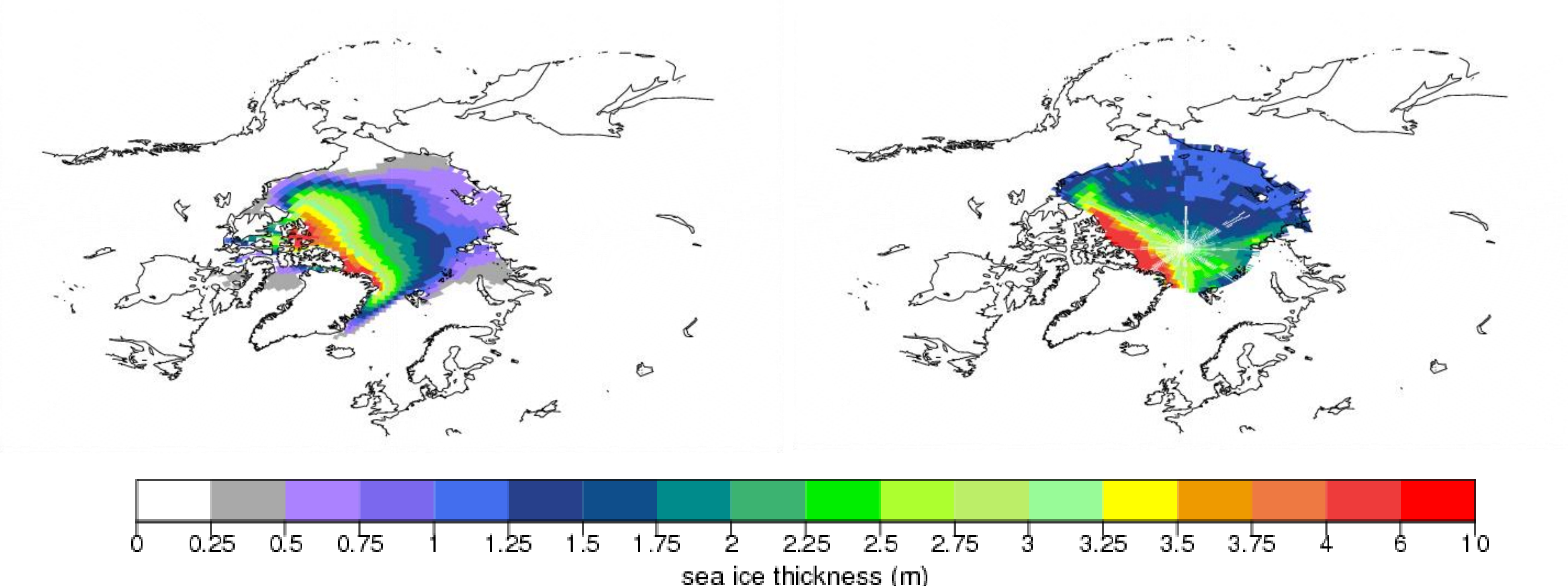
Batté and Doblas-Reyes (2015, Clim. Dyn.)

Seasonal forecasts: Sea ice ics

2003-2007 October-November Arctic sea-ice thickness

Too much ice in central Arctic, too little in the Chukchi and East Siberian Seas.

Reconstruction IceSat



Guemas et al. (2014, Clim. Dyn.)

Seasonal forecasts: Sea ice ics

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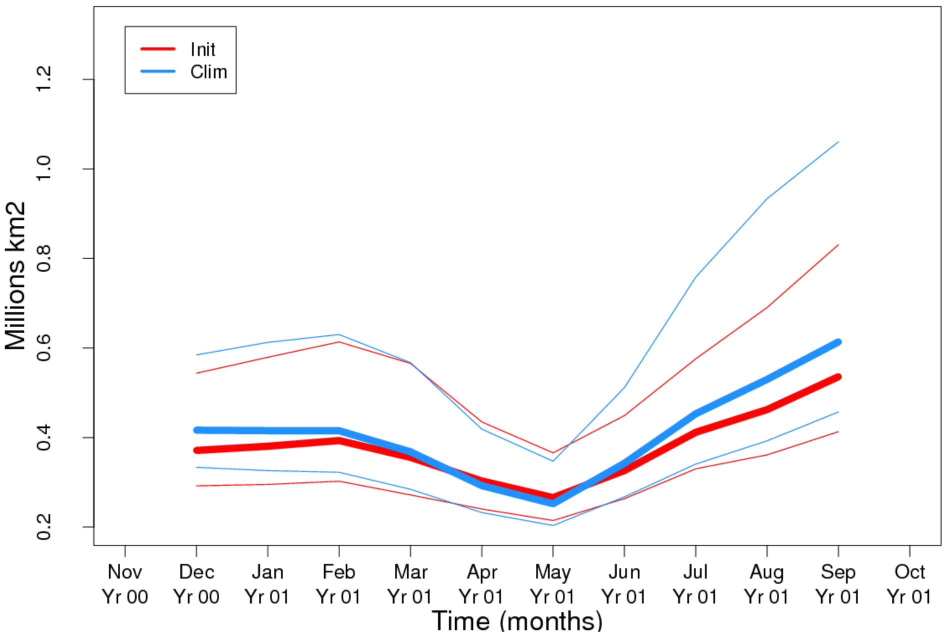
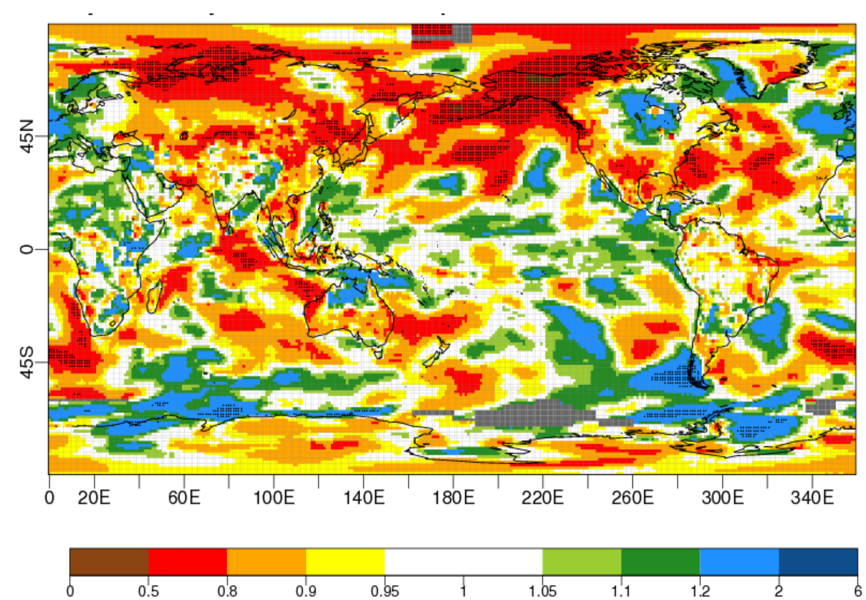
Predictions with EC-Earth2.3 started every November over 1979-2010 with ERAInt and ORAS4 initial conditions, and our sea-ice reconstruction. Two sets, one initialised with realistic and another one with climatological sea-ice initial conditions.

RMSE Arctic sea-ice area



Ratio RMSE Init/Clim hindcasts 2-metre temperature (months 2-4)



Guemas et al. (2015, GRL)

Where to go to with initialization

Aim: creation of sea-ice initial conditions with Ensemble Kalman Filter

Idea: keep track of the model error and its structure by **running 25 members instead of one**

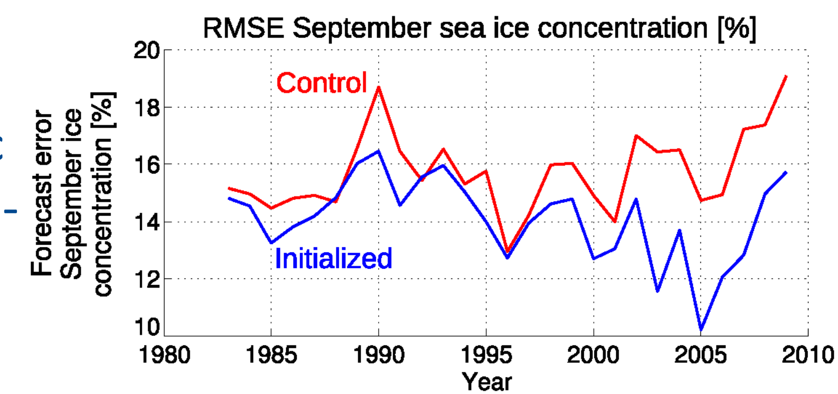
Advantage 1: a first-order approximation of spatial and intervariable relationships is available

Advantage 2: physical consistency guaranteed with linear approximation

Drawback: the associated computational cost is VERY large

We don't start from scratch: the method has been extensively validated in atmosphere-forced mode

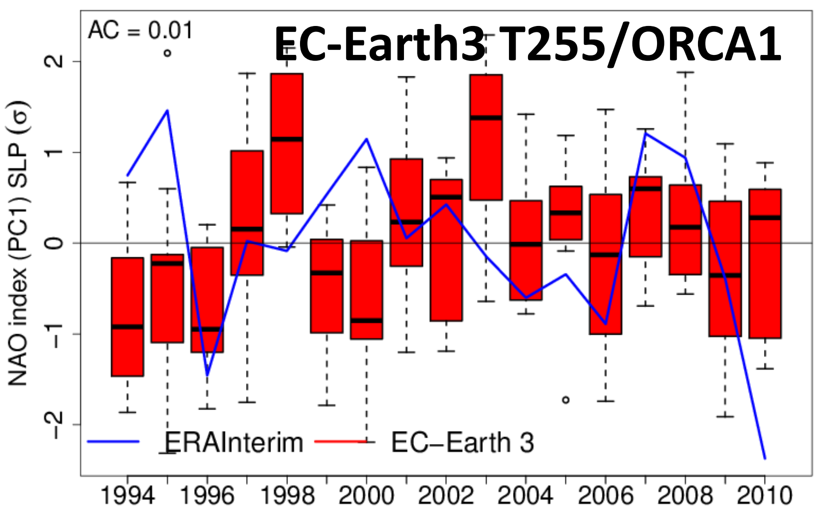
Improvement in seasonal Arctic sea-ice predictions (atmosphere-forced model)

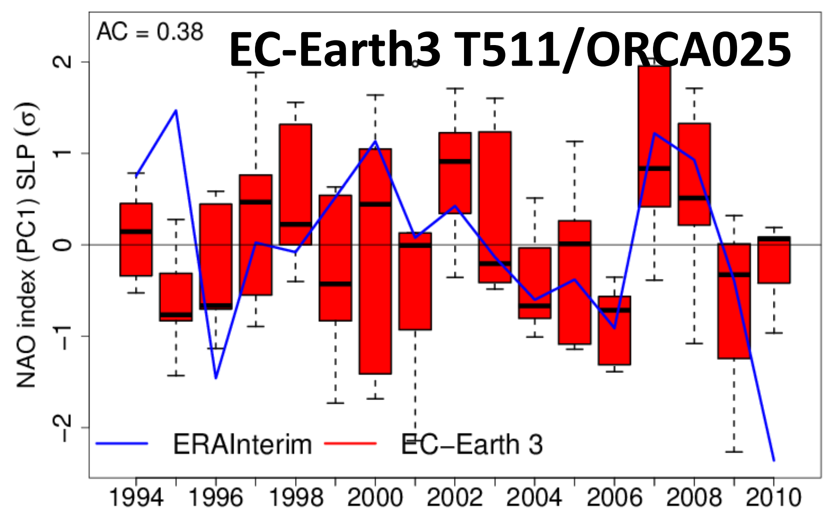


F. Massonnet (IC3, UCL)

Back to model resolution: the NAO

Predictions of DJF NAO with EC-Earth3 at low and high resolution started in November over 1993-2009 with ERA-Interim and GLORYS initial conditions and five-member ensembles. Correlation of the ensemble mean on top left.



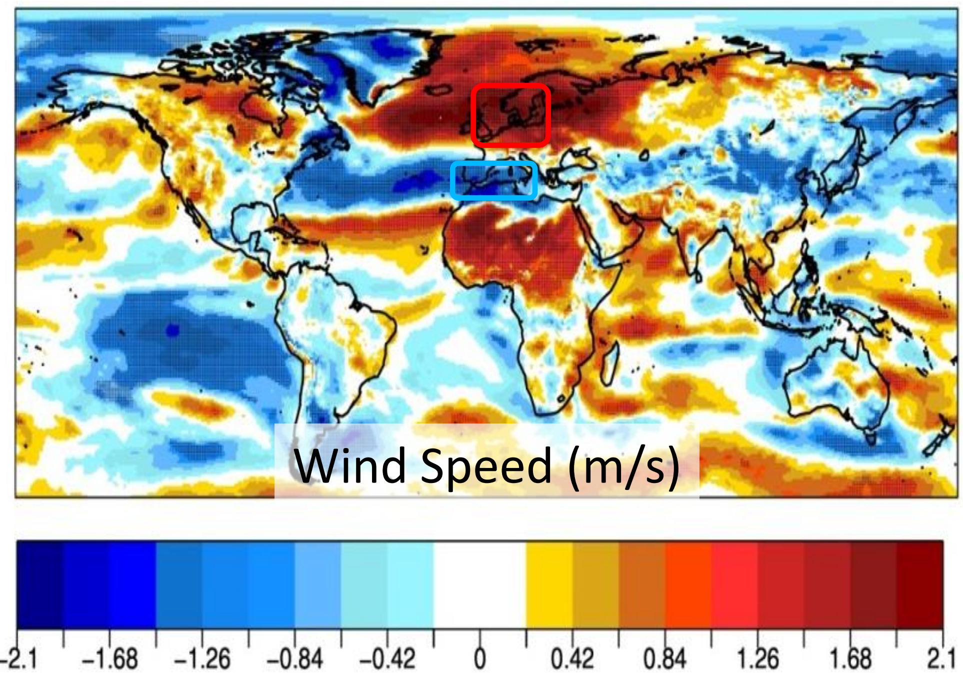


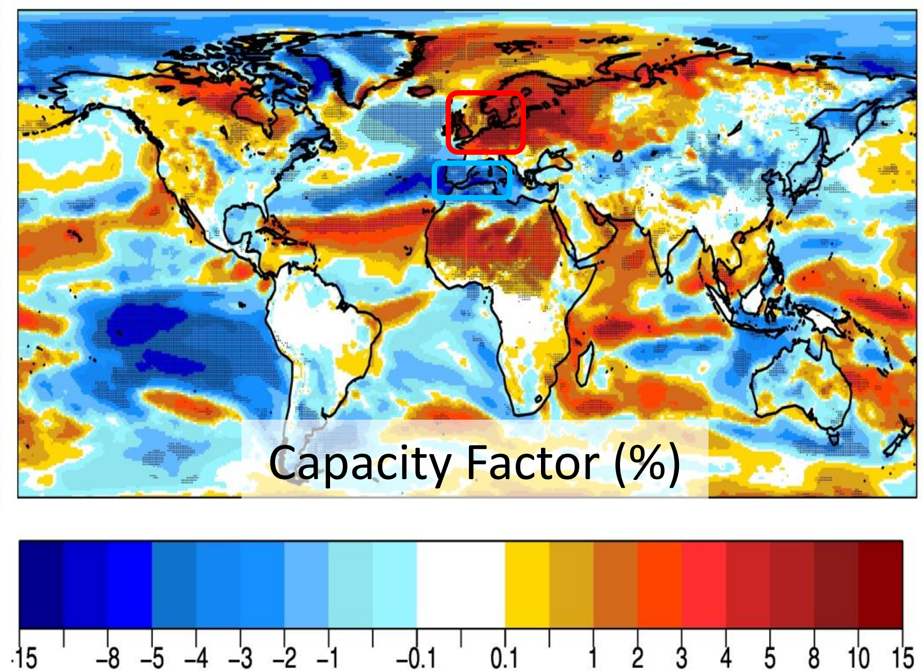
Batté et al. (2014)

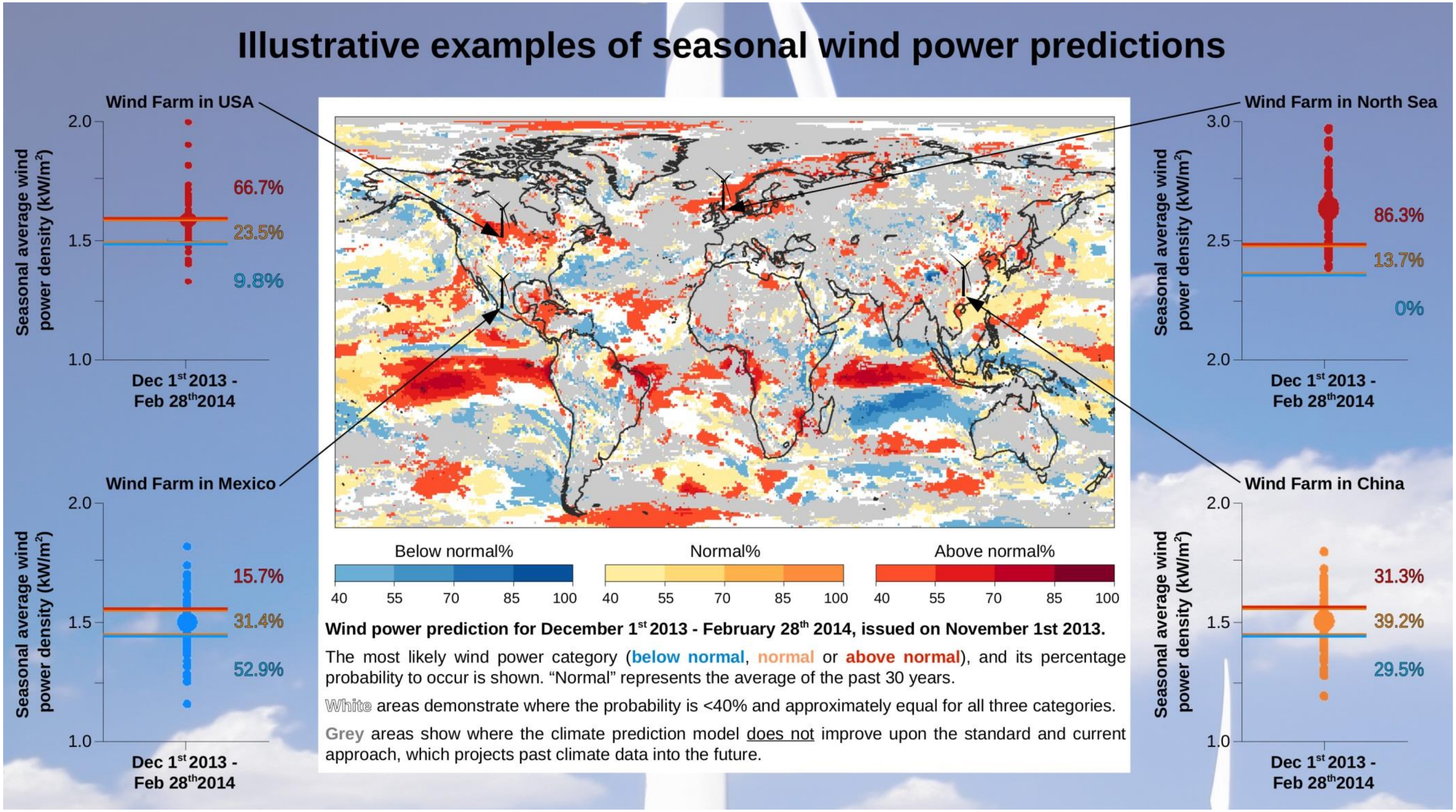
NAO and wind energy

Difference in winter (DJF) standardised 10-metre wind speed (left) and capacity factor (right) for seasons with above normal and below normal North Atlantic Oscillation index.

Daily capacity factor (%) calculated from ERAInterim 10-metre wind speed and temperature data using an idealised power curve, a log scaling law to transform the wind to hub height wind, and a Rayleigh distribution to model diurnal variability.





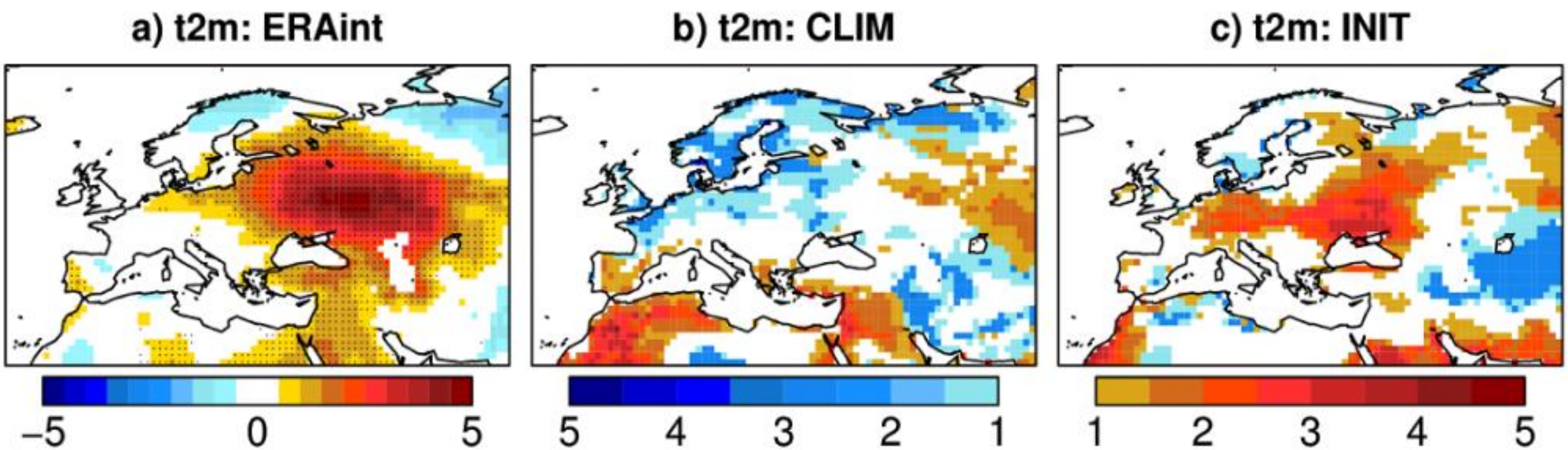


Illustrative examples of seasonal wind power predictions
Wind Farm in USA
Seasonal average wind power density (kW/m²)
2.0
1.5
1.0
66.7%
23.5%
9.8%
Dec 1st 2013 - Feb 28th 2014
Wind Farm in North Sea
3.0
2.5
2.0
86.3%
13.7%
0%
Dec 1st 2013 - Feb 28th 2014
Wind Farm in Mexico
2.0
1.5
1.0
15.7%
31.4%
52.9%
Dec 1st 2013 - Feb 28th 2014
Wind Farm in China
2.0
1.5
1.0
31.3%
39.2%
29.5%
Dec 1st 2013 - Feb 28th 2014
Below normal%
Normal%
Above normal%
40 55 70 85 100
Wind power prediction for December 1st 2013 - February 28th 2014, issued on November 1st 2013.
The most likely wind power category (below normal, normal or above normal), and its percentage probability to occur is shown. "Normal" represents the average of the past 30 years.
White areas demonstrate where the probability is <40% and approximately equal for all three categories.
Grey areas show where the climate prediction model does not improve upon the standard and current approach, which projects past climate data into the future.

Improving temperature forecasts

JJA near-surface temperature anomalies in 2010 from ERAInt (left) and experiments with a climatological (centre) and a realistic (right) land-surface initialisation.

Results for EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.

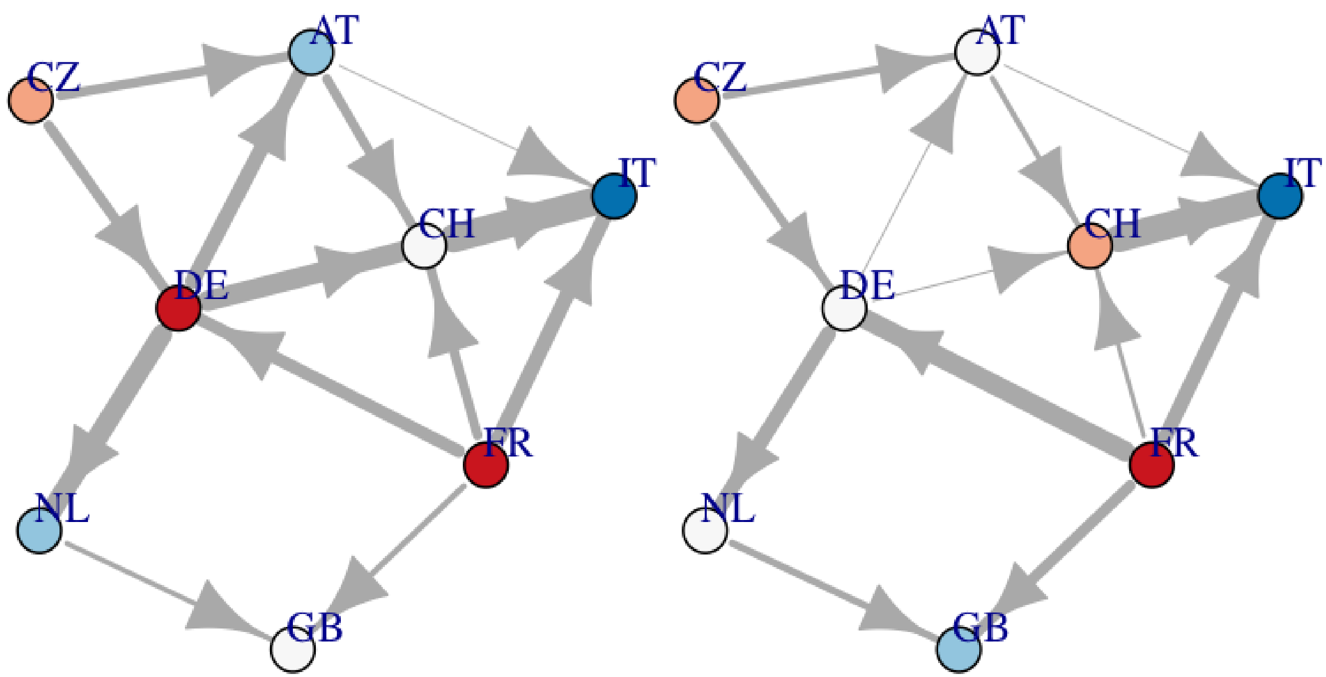


Prodhomme et al. (2015, Clim. Dyn.)

Temperature forecasts for energy

European electricity flows for Jan-Feb (left) and June-July (right). Red nodes are the main exporters and blue the main importers. For clarity only the eight countries with the highest exchange are shown.

Data from ENTSO-E (2003-2014).



M. De Felice (ENEA)

Temperature forecasts for energy

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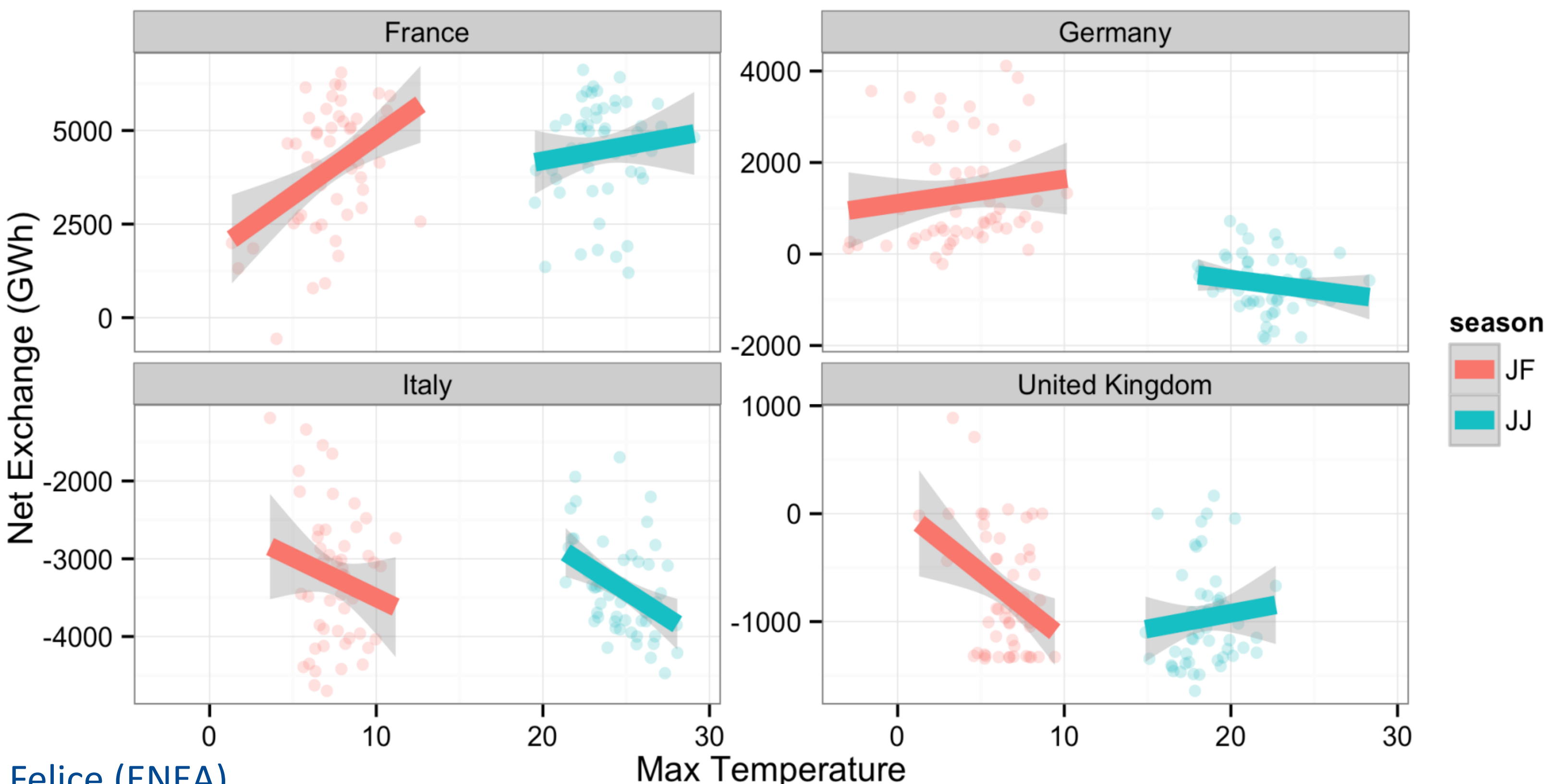
Weather and climate affect exchanges via electricity demand (heating or cooling, from the customer point of view) and RE production.

Data from ENTSO-E (2003-2014).



M. De Felice (ENEA)

Model efficiency

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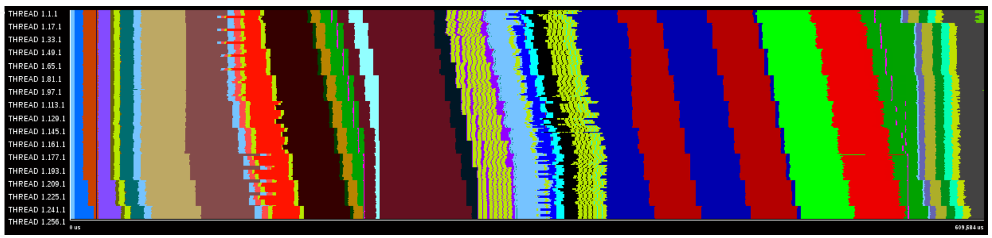
Results from NEMO 3.4 in Marenostrum 3 with the ORCA025 configuration using BSC Performance tools.

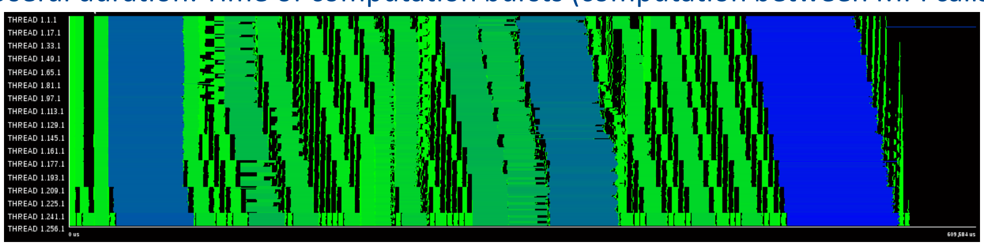
Function instrumentation

Cores (parallel processes)

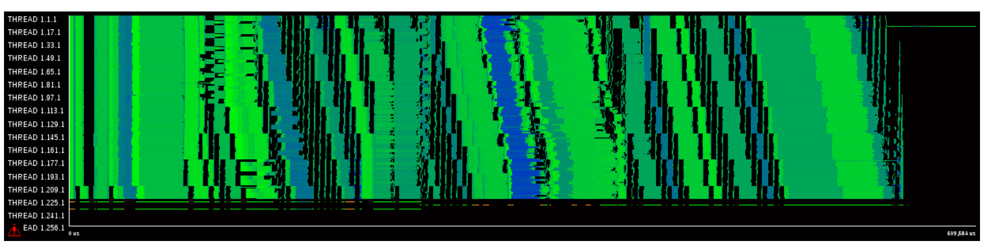


Serial efficiency

Useful duration: Time of computation bursts (computation between MPI calls)



Useful IPC (Instructions per cycle)



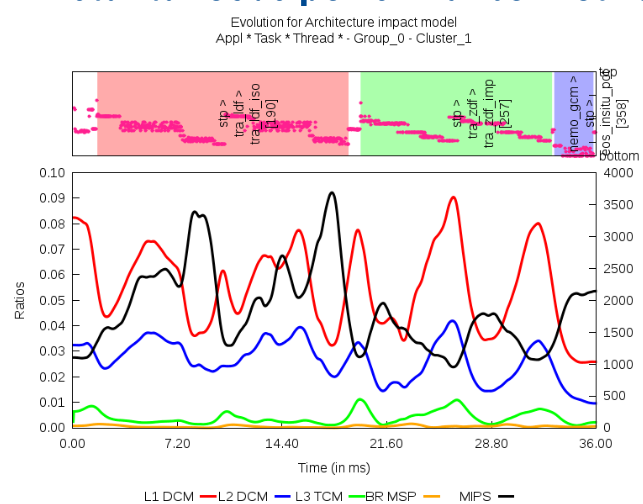
Horizontal axis -> Time component

Parallel efficiency

	Outside MPI	MPI_Recv	MPI_Isend	MPI_Wait	MPI_Allreduce	MPI_Allgather
THREAD 1.236.1	70.43 %	28.58 %	0.12 %	0.18 %	0.69 %	-
THREAD 1.237.1	71.34 %	26.58 %	0.16 %	1.23 %	0.70 %	-
THREAD 1.238.1	72.11 %	26.53 %	0.11 %	0.54 %	0.72 %	-
THREAD 1.239.1	71.49 %	26.94 %	0.10 %	0.79 %	0.68 %	-
THREAD 1.240.1	70.56 %	28.06 %	0.11 %	0.61 %	0.68 %	-
THREAD 1.241.1	89.56 %	0.82 %	0.19 %	0.16 %	0.04 %	9.22 %
THREAD 1.242.1	88.96 %	1.61 %	0.18 %	0.66 %	0.05 %	8.55 %
THREAD 1.243.1	89.06 %	1.71 %	0.13 %	0.40 %	0.05 %	8.66 %
THREAD 1.244.1	88.78 %	2.59 %	0.15 %	0.17 %	0.05 %	8.26 %
THREAD 1.245.1	88.91 %	1.01 %	0.14 %	0.12 %	0.05 %	9.77 %
THREAD 1.246.1	88.74 %	2.42 %	0.14 %	0.14 %	0.05 %	8.51 %
THREAD 1.247.1	88.96 %	1.70 %	0.18 %	0.21 %	0.05 %	8.91 %
THREAD 1.248.1	88.32 %	1.39 %	0.17 %	0.16 %	0.05 %	9.92 %
THREAD 1.249.1	88.14 %	1.43 %	0.13 %	0.20 %	0.07 %	10.03 %
THREAD 1.250.1	88.24 %	1.29 %	0.12 %	0.55 %	0.07 %	9.72 %
THREAD 1.251.1	87.00 %	2.31 %	0.18 %	0.10 %	0.07 %	10.34 %
THREAD 1.252.1	87.58 %	1.92 %	0.13 %	0.15 %	0.08 %	10.13 %
THREAD 1.253.1	87.34 %	1.99 %	0.18 %	0.09 %	0.09 %	10.30 %
THREAD 1.254.1	87.71 %	1.47 %	0.14 %	0.40 %	0.08 %	10.21 %
THREAD 1.255.1	87.73 %	1.65 %	0.18 %	1.36 %	0.08 %	8.00 %
THREAD 1.256.1	87.60 %	2.53 %	0.17 %	0.21 %	0.07 %	9.42 %
Total	18,718.18 %	4,259.56 %	61.57 %	2,133.74 %	276.02 %	150.94 %
Average	73.12 %	16.64 %	0.24 %	8.33 %	1.08 %	9.43 %
Maximum	89.56 %	28.60 %	0.31 %	23.62 %	1.30 %	10.34 %
Minimum	69.38 %	0.82 %	0.10 %	0.06 %	0.04 %	8.26 %
StDev	4.00 %	8.68 %	0.04 %	8.11 %	0.32 %	0.69 %
Avg/Max	0.82	0.58	0.77	0.35	0.83	0.91

MPI Stats reflect the percentage of time invested in computation for each thread. Total stats give the communication efficiency and the load balance.

Instantaneous performance metrics



M. Castrillo (BSC)

Workflows: Autosubmit

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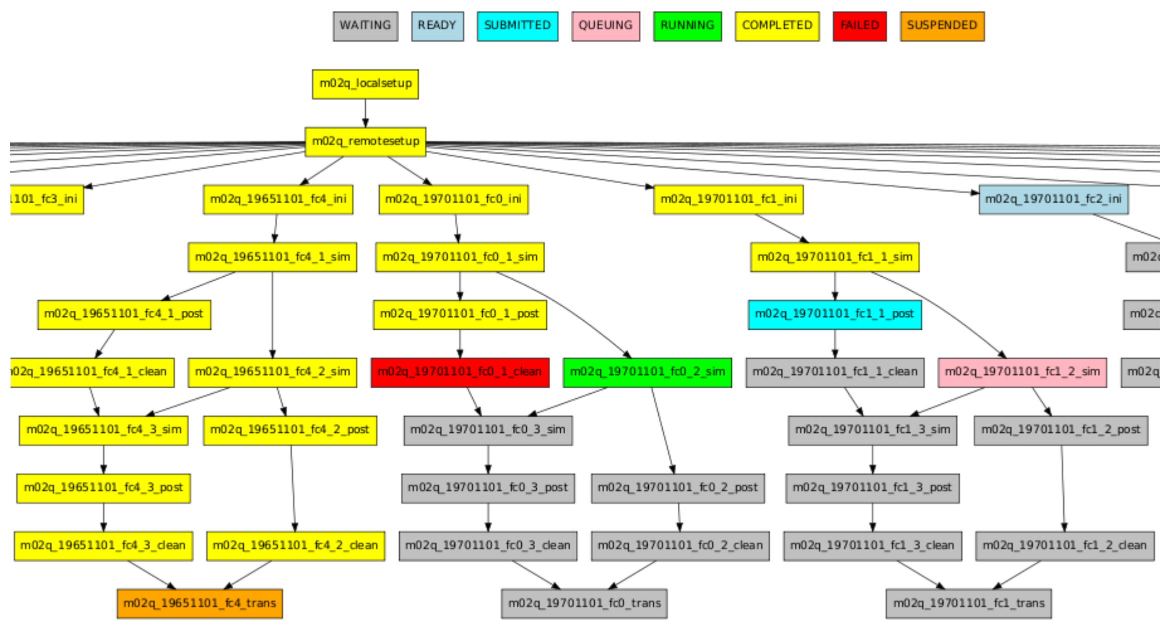
- **Automatisation:** Preparing and running, postprocessing and output transfer, all managed by Autosubmit. No user intervention needed.
- **Provenance:** Assigns unique identifiers to each experiment and stores information about model version, configuration options, etc.
- **Failure tolerance:** Automatic retrials and ability to repeat tasks in case of corrupted or missing data.
- **Versatility:** Currently run EC-Earth. NEMO and NMMB models on several platforms.

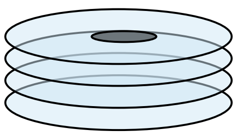
Workflow of an experiment monitored with Autosubmit (yellow = completed, green = running, red = failed, …)



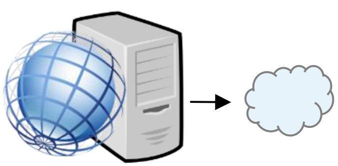
D. Manubens, J. Vegas (IC3)

S2dverification is an R package to verify seasonal to **decadal** forecasts by comparing experimental data with observational data. It allows analysing data available either locally or remotely. It can also be used online as the model runs.

s2dverification package



LOCAL STORAGE



ESGF NODE
or
OPeNDAP SERVER

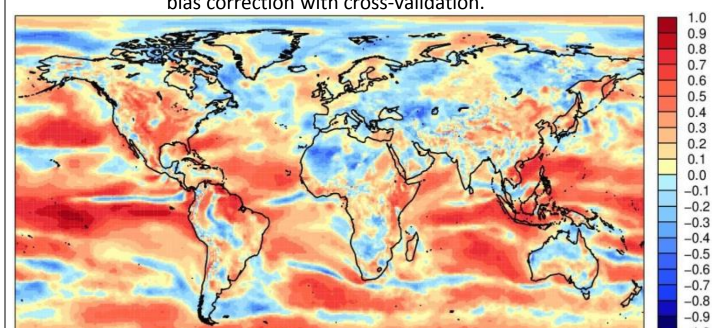
- Supports datasets stored locally or in ESGF (OPeNDAP) servers.
- Exploits multi-core capabilities
- Collects observational and experimental datasets stored in multiple conventions:
  - NetCDF3, NetCDF4
  - File per member, file per starting date, single file, …
  - Supports specific folder and file naming conventions.

BASIC STATISTICS

SCORES
Correlation, ACC, RMSSS, CRPS, …

PLOTS

Anomaly Correlation Coefficient. 10M Wind Speed ECMWF S4 1 month lead with start dates once a year on first of November and Era-Interim in DJF from 1981 to 2011. Simple bias correction with cross-validation.



Summary

- Requests for climate information for the next 30 years as a continuous stream come from a broadening range of users and should be addressed from a climate services perspective.
- Different tools are available to provide near-term climate information (global and regional projections, seasonal and decadal predictions, empirical systems, etc). Merging all this information into a reliable, unique source is a problem still not solved.
- The climate-services community is maturing quickly and there are successful stories of interactions with users.
- None of this will materialize without appropriate investment in observational networks and reduction of all aspects of model error, plus infrastructures that rationalize the investments in climate-modelling research.